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ANALYSIS OF INDIAN STOCK MARKET VOLATILITY USING SYMMETRIC AND ASYMMETRIC GARCH MODELS

Prof. Pushpa M. Savadatti
Dept of Economic Studies & Planning
Kalburgi, Karnataka

Abstract

The present study analysed the volatility pattern of the Bombay Stock Exchange (BSE) based on the daily return series of the S&P BSE all cap index covering the period 16-09-2005 to 09-03-2018 using both symmetric and asymmetric Generalised Auto Regressive Conditional Heteroscedasticity (GARCH) models. All the estimated coefficients of the ARCH and GARCH terms are having expected sign and statistically significant indicating that the daily return series of BSE all cap index are exhibiting high volatility and volatility clustering behaviour. The asymmetric GARCH model results showed enough evidence for the presence of leverage effect in the daily return series. All the estimated models fitted the data well. The results of the analysis are helpful for investors and other stake holders of the stock market in their decision making.

Key words: GARCH models, Leverage effect, Volatility, Unit root, daily return series

INTRODUCTION

The capital markets are playing important role in the development of economies. It is considered as an engine of growth as it is an essential source of capital for business activities.

Capital markets around the globe are integrated due to the globalisation resulting into enhanced flow of capital across the globe. The stock market provides ample opportunities for investors for investment and also provides the required resources for numerous economic activities of a country. But these markets are characterised by the volatility as the they are sensitive to various domestic and international factors. Given the importance of stock markets in the changed global scenario modelling volatility of financial time series has gained lot of interests among the researchers. The stock market volatility is varying with time and it displays the character of volatility clustering. The number of models have been developed over a period of time to model the volatility dynamics of the stock markets and family of GARCH models are popular among them. These developments encouraged lot of research about volatility of financial time series data. The present study aims at examining the volatility dynamics of S&P BSE all cap index. The Bombay Stock Exchange is known as the oldest Stock Exchange in Asia. The S&P BSE all cap index is a broad index covering more than 95 percent of the total market capitalisation and consisting of more than 700 stocks that are listed on BSE (www.bseindia.com). The analysis will help the investors, policy makers and regulatory authorities in making investment, policy and regulatory decisions.

LIETRATURE REVIEW

The number of studies have been conducted across the globe using family of GARCH models for analysing the volatility of time series. The some of the studies which helped in designing the research framework for the present analysis have been discussed here. The competence of the Indian stock market was analysed with the help of Augmented Dicky Fuller (ADF) test, Phillips-Perron (PP) test and Generalised Auto Regressive Conditional Heteroscedasticity (GARCH) model of order (1,1) (Dsouza & Mallikarjunappa, 2015). Another study analysed the stock return volatility of the Nigerian Stock Exchange with the help of family of GARCH models (symmetric and asymmetric) found that there existed high persistent volatility for the NSE return series and leverage effect was not present for the return series (Adesina, 2013). The volatility dynamics of the five sectoral indices of the National Stock Exchange of India was done using three GARCH models and based on the results it was suggested that risk averse investors can invest in IT, Bank and FMCG sectors and may avoid Auto and reality sectors stocks which were characterised by the persistent volatility (Singh & Teena, 2018). The volatility of the daily returns of the Kenyan stock market was estimated with the help of GARCH models and results showed the highly persistent volatility process and the presence of the leverage effect in the NSE return series (Maqsood, Safdar, Shafi & Lelit, 2017). Both symmetric and asymmetric GARCH models were used to investigate the behaviour of stock return volatility for Amman Stock Exchange of Jordan and results suggested that the symmetric ARCH and GARCH models captured the features of stock exchange and provided enough evidence for the volatility clustering and leptokurtic (Najjar, 2016). Volatility analysis in daily return series of Khartoum Stock Exchange of Sudan was done using both symmetric and asymmetric GARCH models and results showed that the conditional variance followed the explosive process and found enough evidence for the existence of risk premium in return series (Ahmed & Suliman, 2011). Based on the literature of the available work the methodology for the present work is worked out and in the following section.

RESEARCH METHODOLOGY

Data Description

The time series data pertaining to S&P BSE All Cap Index which is a wide-ranging index encompassing more than 95 percent of the total market capitalisation and including more than 700 stocks that are listed on the BSE (bseindia.com) are used for the present analysis. The S&P BSE All Cap Index will give image of overall market measurement. Hence, data on closing prices of S&P BSE all cap index are used for the present analysis. The daily data on closing prices were collected from the data source of the BSE website – bseinida.com covering the period 16-09-2005 to 09-03-2018 resulting into 3094 observations excluding public holidays. The data were transformed into daily returns of the closing prices with the help of the following formula for further analysis (Savadatti, 2018)

$R_t = log\left(\frac{P_t}{P_{t-1}}\right)$ ---------------------------------- (1)

Here R_t refers to the daily returns of the S&P BSE all cap index, P_t is daily closing price during 't' period and P_{t-1} is daily closing price during 't-1' period. E-view statistical software is used for the data analysis.

Tools and Techniques used

Descriptive Statistics

To know the distributional properties of the daily return series under consideration descriptive statistics like skewness, kurtosis, Quantile-Quantile plot, mean, variance and many more are used.

Stationarity Tests

It is essential to know whether the series under consideration are stationary or not before proceeding for further analysis. For this purpose, tests like Phillips-Perron (P-P, 1987) tests, Augmented Dicky Fuller (ADF, 1988) and correlogram of the residuals are adopted to test the stationarity of the daily closing prices of BSE index.

Heteroscedasticity Tests

The purpose of the present analysis is to study the volatility aspect of the series under consideration that requires testing for existence of the Auto Regressive Conditional Heteroscedasticity (ARCH effect) in residuals of the daily returns series using Lagrange Multiplier (LM) test. The residuals required for this testing can be calculated by running the any of the mean equations AR (1), MA (1) or ARMA (1,1) depending on the suitability.

GARCH Models

In financial time series data analysis Generalised Auto Regressive Conditional Heteroscedasticity (GARCH) models are used extensively to model the volatility in the stock markets. In the present analysis also different GARCH models have been used to model the volatility in daily returns of S&P BSE all cap index. The models used for the analysis are GARCH (1,1), EGARCH (1,1), PGARCH (1,1) and TGARCH (1,1). GARCH (1,1) model is used for symmetric volatility analysis and remaining models are employed for studying the asymmetric volatility in the concerned stock market. In GARCH models it is necessary to estimate two equations, conditional mean equation and conditional variance equation. Conditional mean equation given as below is used for estimating the family of GARCH models

$R_t = \mu + \emptyset R_{t-1} + \varepsilon_t$; Mean Equation -------------------------------- (2)

Here R_t measures daily return of BSE all cap stock index at time t, μ is intercept and ε_t is residual return. The conditional variance equations adopted for different GARCH models are explained below.

GARCH (1,1) Model

The conditional variance equation (Bollerslev,1986) adopted for capturing the symmetric volatility in BSE all cap index is given in equation (3)

$\sigma_t^2 = \varphi + \propto \varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$ ---------------------- (3)

Here, $\varphi > 0, \propto \geq 0, \beta \geq 0$ and σ_t^2 is the conditional variance for the BSE all cap daily return series. The ε_{t-1}^2 is the lagged ARCH term and σ_{t-1}^2 is lagged GARCH term for BSE daily return series under consideration. The coefficients $\propto$ and β indicate ARCH and GARCH parameters respectively. If the sum of ARCH and GARCH parameters ($\propto + \beta$) is near to one indicates volatility persistence and clustering behaviour and if the sum is less than one means GARCH process is mean reverting and volatility decays over time (Savadatti, 2018). This is a symmetric model capturing only the magnitude of the volatility irrespective of their sign positive or negative.

Asymmetric GARCH Models

It is observed that bad news influences strongly the asset price in the stock market compared to good news. There appears to be negative association between volatility and returns. When returns increase volatility decreases and vice versa. This tendency of the volatility is known as the leverage effect (Zakaria, Abdalla & Winker, 2012). The symmetric GARCH models may not be able to capture the leverage effects present in the stock returns. Hence, in literature number of models have been developed by experts to capture this leverage effect and are known as asymmetric models. These models have been used in the present analysis to capture the asymmetric volatility present in the stock markets.

Exponential GARCH - EGARCH (1,1) Model

EGARCH model (Nelson, 1991) captures the leverage effect (asymmetric volatility) in the data series. This model is used in the present study to capture the asymmetric influence of volatility shocks in the BSE all cap daily return series. The first equation to be estimated is conditional mean equation of the specification mentioned in equation (2) stated above and second equation is conditional variance equation as specified below

$\ln(\sigma_t^2) = \varphi + \propto \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \beta \ln \sigma_{t-1}^2 - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ ---------------------(4)

Here $\propto$ is the ARCH coefficient, β is the GARCH coefficient and γ is the leverage effect parameter. If $\gamma = 0$ the model will be reduced to symmetric GARCH (1,1) model. If $\gamma < 0$ and significant statistically means there exists leverage effect. It means negative shocks will have bigger influence on the next period conditional variance than positive shocks and vice versa.

Power GARCH - PGARCH (1,1) Model

The PGARCH model (Ding, Engle and Granger, 1993) is another asymmetric model where standard deviation is modelled as against variance. The specification of PGARCH model is given below

$\sigma_t^\delta = \varphi + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta$ -------------------------------- (5)

Where $\propto$ is the ARCH parameter, β is the GARCH parameter and γ is the leverage parameter and δ is the parameter for the power term so that $\delta > 0$. If δ takes value two then the above model reduces to GARCH model that deals with leverage effect. If δ assumes value one then the model estimates conditional standard deviation in place of conditional variance.

Threshold GARCH – TGARCH (1,1) Model

Third important asymmetric GARCH model is TGARCH also recognized as GJR model (Glosten, Jagannathan &Reunkie, 1993; Zakoian, 1994) deals with leverage effect and the conditional variance equation of the model is detailed below

$\sigma_t^2 = \varphi + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2$ ---------------------------- (6)

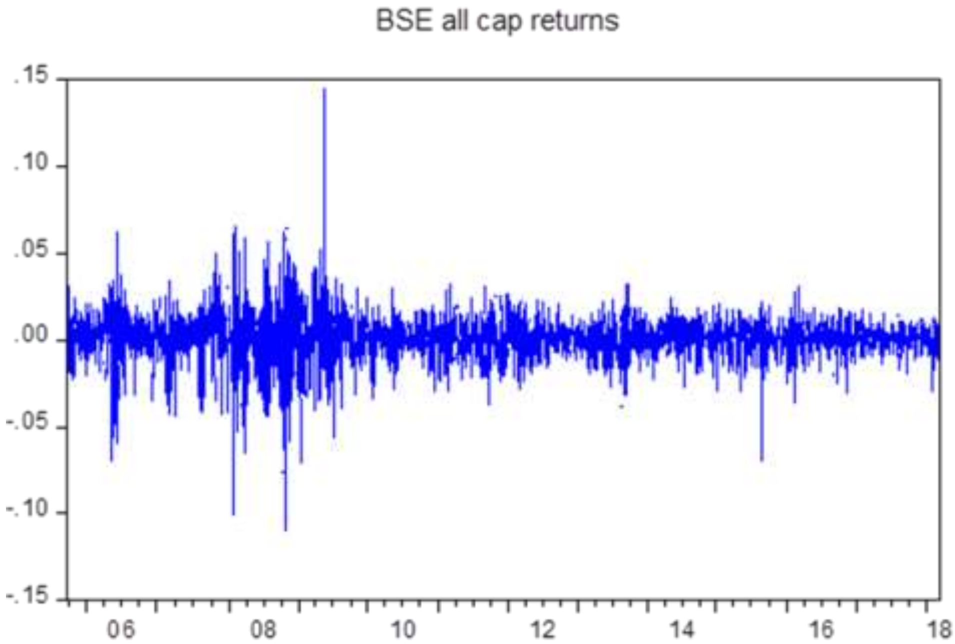
Where, Where $\propto$ represents the ARCH parameter, β the GARCH parameter and γ is identified as leverage parameter. When $I_{t-1} = 0$, the effect on volatility is α (shock is positive or good news) and if $I_{t-1} = 1$, the effect on volatility is $\propto +\gamma$ (shock is negative or bad news). If $\gamma > 0$ and significant then negative shocks have greater impact on conditional variance than positive shocks.

RESULTS

Descriptive Statistics

In this section the distributional properties of the daily return series of BSE all cap index is analysed with the help of the descriptive statistics. The plot of the daily returns is presented in Figure 1.

Figure 1: BSE (all cap) Daily Return Series



Source: Data Analysis

It may be observed from the Figure-1 that the daily return series exhibit lot of volatility during the study period. High volatility is noticed during 2006 to 2009 and this high volatility is sustained for a long and then relatively low volatility is observed in the remaining period except around the period 2015. It may be noted that the periods of high volatility followed by periods low volatility for a longer period resulting into volatility clustering. The summary statistics calculated for the data is shown in Table 1.

Table 1: BSE all cap Index Daily Returns Descriptive Statistics	
Mean	0.000457
Median	0.001278
Maximum	0.144729
Minimum	-0.110746
Std. Dev.	0.013980
Skewness	-0.303561
Kurtosis	11.89938
Jarque-Bera	10250.96
Probability	0.000000
Observations	3092
Source: Data Analysis	

The daily returns are in the range of -0.110746 to 0.144729. The mean returns are around 0.000457. The value of Kurtosis is larger than 3 and Skewness is around -0.3 indicating that the series under consideration are leptokurtic with left tail. The value for Jarque-Bera (JB) test is very high resulting into very low probability indicating that the daily return series are not confirmed to normal distribution. The graph of Quantile-Quantile (Q-Q) is shown in Figure 2.

Figure 2: Quantile-Quantile Plot of Daily Return Series (BSE all cap)

Source: Data Analysis

In Figure 2 it may be observed that the plot in blue line follows the S shape rather than straight line indicating that the series are not normally distributed hence, endorsing the results of the descriptive statistics about the distributional properties of the daily return series under consideration.

Stationarity Tests

The daily return series of the BSE all cap index was tested for the unit root using ADF and PP tests and the results are presented in Table 2.

Table 2: Stationary Test Results for Daily Return Series (BSE all cap)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-49.68161	0.0001
Test critical values:	1% level	-3.432276	
	5% level	-2.862277	
	10% level	-2.567206	
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-49.56008	0.0001
Test critical values:	1% level	-3.432276	
	5% level	-2.862277	
	10% level	-2.567206	
*MacKinnon (1996) one-sided p-values; Source: Data Analysis			

The t-statistics calculated for the series are higher than the critical values at 1% level of significance and the calculated probability is < 0.01 specifying that the null hypothesis of unit root is rejected and series are stationary according to ADF test. The similar results are obtained for PP test also wherein the computed Adj. t-statistics is quite high compared to critical values resulting into acceptance of alternative hypothesis of no unit root. So, it may be concluded that the daily return series are stationary.

Heteroscedasticity Test

In order to model the volatility pattern, present in the return series it is necessary to examine whether there exists Auto Regressive Conditional Heteroscedasticity (ARCH) effect in the residuals with the help of Lagrange Multiplier (LM) test and the results are presented in Table 3.

Table 3: Heteroscedasticity Test - ARCH-LM (Daily Returns)				
BSE Returns	**F-statistic**	75.27364	**Prob. F(5, 1065)**	0.0000
	Obs*R-squared	336.0500	**Prob. Chi-Square(5)**	0.0000
Source: Data Analysis				

The value of F-statistics is large and the probability is very low resulting into rejection of null hypothesis of no ARCH effect in residuals. The correlogram of the squared residuals is shown in Figure 3, also revealed that all the autocorrelations and partial autocorrelations are all significant as the corresponding probabilities are very low signalling the presence of ARCH effect in residuals.

Figure 3: Correlogram of Squared Residuals for Daily Returns

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.189	0.189	110.80	0.000
		2	0.226	0.198	269.25	0.000
		3	0.194	0.132	386.11	0.000
		4	0.219	0.142	534.33	0.000
		5	0.129	0.026	585.76	0.000
		6	0.146	0.048	652.19	0.000
		7	0.169	0.082	740.59	0.000
		8	0.109	0.007	777.33	0.000
		9	0.164	0.080	860.64	0.000
		10	0.206	0.122	991.94	0.000

Source : Data Analysis

Results of GARCH Models

ARCH-LM test suggested the presence of heteroskedasticity in residual series hence, we can procced for modelling volatility in daily return series of BSE all cap index. Generalised Auto Regressive Conditional Heteroskedasticity (GARCH) models are used widely in literature to model the volatility. These models are categorised into two symmetric and asymmetric models. Symmetric models consider only magnitude of volatility irrespective of the sign but in asymmetric volatility models conditional variance depends on the magnitude of volatility along with signs. In the present analysis also both symmetric and asymmetric models are used and the results of the fitted models are presented in Table 4.

Table 4: GARCH Models Result			
GARCH (1,1)			
Mean Equation	**Parameters**	**Coefficient**	**Prob.**
	μ	0.001103***	0.0000
	Ø (AR term)	0.107785***	0.0000
Variance Equation	φ	2.35E-06***	0.0001
	∝ (ARCH effect)	0.096237***	0.0000
	β (GARCH effect)	0.891998***	0.0000
	$\propto +\beta$	0.988235	
EGARCH (1.1)			
Mean Equation	μ	0.000843***	0.0000
	Ø (AR term)	0.123933***	0.0000
Variance Equation	φ	-0.370915***	0.0000
	∝ (ARCH effect)	0.186973***	0.0000
	β (GARCH effect)	0.974849***	0.0000
	$\propto + \beta$	1.161822	
	γ (Leverage effect)	-0.116397***	0.0000
PGARCH (1,1)			
Mean Equation	μ	0.000831***	0.0000
	Ø (AR term)	0.124629***	0.0000
Variance Equation	φ	9.91E-05	0.2301
	∝ (ARCH effect)	0.100467***	0.0000
	β (GARCH effect)	0.888285***	0.0000
	$\propto + \beta$	0.988752	
	γ (Leverage effect)	0.608861***	0.0000
	δ (Power parameter)	1.262540***	0.0000
TGARCH (1,1)			
Mean Equation	μ	0.000836***	0.0000
	Ø (AR term)	0.119912***	0.0000
Variance Equation	φ	3.52E-06***	0.0000
	∝ (ARCH effect)	0.022026**	0.0513
	β (GARCH effect)	0.874565***	0.0000
	$\propto + \beta$	0.896591	
	γ (Leverage effect)	0.158235***	0.0000
***,**: indicate significance at 1% and 5% level respectively Source: Data Analysis			

Estimation of GARCH models contains estimation of two equations conditional mean equation and conditional variance equation and the results of the same are discussed here. GARCH (1,1) results in Table 4 indicate that all the coefficients of mean and variance equations are significant. In conditional variance equation the coefficients of ARCH (∝) and GARCH (β) terms have expected sign and also significant at 1 per cent level. This means lagged conditional variance and lagged squared disturbance terms significantly influence the current volatility in daily return series of the BSE all cap index. News about the volatility from previous periods impact the current volatility. The sum of ARCH and GARCH coefficients ($\propto + \beta$) is close to one indicating that shocks are persistent but not explosive signalling mean reverting process.

The asymmetric EGARCH (1,1) model is estimated to examine the presence of leverage effect in daily return series of BSE all cap index. The results of the EGARCH model are presented in Table 4. All the estimated coefficients of the EGARCH model are statistically significant at 1 per cent level. The γ which captures the leverage effect (asymmetric effect) is having negative sign and statistically significant indicating that previous period's negative shocks (bad news) have greater impact on the next period's conditional variance than the positive shocks (good news) of the same magnitude. This indicates the presence of leverage effects in daily return series of the BSE all cap index during study period.

The another asymmetric model estimated to test the presence of leverage effect in daily return series is PGARCH (1,1), the results of which are shown in Table 4. All the estimated coefficients are statistically significant at 1% level. The leverage effect captured by γ is having positive sign and significant at 1% level indicating that the effect of previous period's positive news is greater than the effect of negative news of the same magnitude or positive shocks are associated with higher volatility than negative shock.

The third model estimated to test the asymmetry in the volatility of daily return series is TGARCH (1,1) and results show that all the estimated coefficients are statistically significant and the sum of ARCH and GARCH terms is less than one signalling mean reverting variance process. The leverage effect captured by the γ coefficient is positive and significant at 1 % level which shows the presence of asymmetry effect during the study period. The bad news is having larger effect on the volatility (conditional variance) compared to the good news of the same magnitude.

The results of the model adequacy tests are presented in Table 5.

Table 5: Heteroscedasticity Test - ARCH-LM

GARCH(1,1)			
F-statistic	0.969075	Prob. F(5, 1065)	0.4352
Obs*R-squared	4.847191	Prob. Chi-Square(5)	0.4348
EGARCH(1,1)			
F-statistic	1.020574	Prob. F(5, 1065)	0.4037
Obs*R-squared	5.104355	Prob. Chi-Square(5)	0.4033
PGARCH(1,1)			
F-statistic	0.949171	Prob. F(5, 1065)	0.4478
Obs*R-squared	4.747782	Prob. Chi-Square(5)	0.4474
TGARCH(1,1)			
F-statistic	0.580997	Prob. F(5, 1065)	0.7146
Obs*R-squared	2.907903	Prob. Chi-Square(5)	0.7142

Source: Data Analysis

ARCH-LM test was applied to the residuals of the GARCH models estimated as above to test the presence of the ARCH effect. The estimated statistics clearly indicate the absence of ARCH effect in residuals in all the four estimated GARCH models as the probability is > 0.05 in all the cases signalling the acceptance of null hypothesis of no ARCH effects. We do not find the evidence of ARCH effects in residuals hence, fitted models are well specified.

CONCLUSION

The present study analysed the volatility present in the daily return series of the BSE all cap index. To model stock return volatility five GARCH models were considered. Both symmetric and asymmetric univariate Generalised Auto Regressive Conditional Heteroscedasticity (GARCH) models were estimated to capture volatility clustering and leverage effects in the daily return series of the BSE all cap index. The models considered are symmetric GARCH(1,1) and asymmetric models Exponential GARCH(1,1), Power GARCH(1,1) and Threshold GARCH(1,1). Symmetric GARCH models capture the symmetric effect of past shocks whereas asymmetric models capture asymmetric effects.

The data analysis revealed that the daily return series of BSE all cap index do not exhibit normality and there existed the ARCH effect in the residuals hence, presented enough evidence for modelling volatility in the daily return series with the help of GARCH models. The estimated parameters of the GARCH (1,1) model are statistically significant and sum of the ARCH and GARCH coefficients are near to one indicating the persistence and gradual decay of the shocks to volatility. The coefficients of all ARCH terms in the asymmetric GARCH models are significant showing that the news about previous period volatility is strongly impacting the current period daily returns of BSE all cap index. The all GARCH terms are also positive and statistically significant at 1 percent level representing volatility clustering and current period conditional variance is significantly influenced by the previous period volatility. The sum of the ARCH and GARCH coefficients are though less than one but near to one indicating the volatility persistence and volatility clustering behaviour. The values of γ which show the leverage effect are having expected sign and statistically significant in all the estimated asymmetric models giving significant evidence for the existence of the leverage effect in the daily return series of BSE all cap index. The results are of great importance to regulators and policy makers of the BSE.

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